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Incremental Capacity Analysis Applied on Electric Vehicles for Battery State-of-Health Estimation

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***Abstract*—The State-of-Health (SoH) of Electric Vehicle (EV) batteries is important for the EV owner and potential buyer of second hand EVs. The Incremental Capacity Analysis (ICA) has by several researchers proven to be a promising SoH estimation method for lithium-ion batteries. However, in order to be practical useable, the method needs to be feasible on a pack or EV level and not only on an individual cell level. Therefore, the purpose of this paper is to demonstrate the feasibility of the ICA method on real EVs. Nickel Manganese Cobalt (NMC) cells used in BMW i3 EVs and Lithium Manganese Oxide (LMO) used in Nissan Leaf EVs have been tested both on the cell level and on car level. The results are consistent and the characteristic peaks and valleys of the ICA on car level match with the same on cell level. A root-mean-square-error of 1.33 % and 2.92 % has been obtained for the SoH estimation of the NMC and LMO type, respectively. It is therefore concluded that the ICA method is also applicable to the car level for battery SoH estimation.**

***Keywords*—Incremental capacity analysis; state-of-health; estimation; lithium-ion battery; electric vehicle.**

I. Introduction

The State-of-Health (SoH) of electric vehicle (EV) lithium-ion batteries is of huge concern for EV owners and potential buyers of secondhand EVs as the battery of the EV is one of the most expensive components of the EV. There is no universal definition of SoH but capacity fade and internal resistance rise are the main contributors to SoH reduction. Capacity fade means shorter driving range which is more critical for a buyer of a used EV than a marginal reduction in acceleration performance due to increased internal resistance. In this article SoH refers to the relation between nominal new capacity and actual capacity, and a new battery is therefore at 100% SoH. The challenge is to assess the actual available capacity in an EV.

Incremental Capacity Analysis (ICA) is often being used for battery degradation analysis and identification due to the non-destructive nature of the method [1], [2]. However, ICA also turned out to be a promising method for battery SoH estimation and several researchers have demonstrated that the characteristic peaks and valleys, which appear when applying the ICA method, can be used to estimate the actual capacity of the battery.

In [3], ICA and Differential Voltage Analysis (DVA) was applied on three 60 Ah Lithium Iron Phosphate (LFP) cells exposed to cycling aging. It was demonstrated that two Feature Points (FP) always were present at the same State-of-Charge (SoC) level. The accumulated charge between those two FPs can be used for capacity estimation with an error band of 2 %. In [4], ICA was applied on 10 Ah Nickel Manganese Cobalt (NMC) cells exposed to cyclic aging at different charging rates and temperatures. A peak was identified, who's values and voltage position was directly related to the actual capacity of the cells. A method based on Multi Island Generic Algorithm (MIGA) and Gaussian Process Regression (GPR) was developed and the maximum error of the SoH prediction was reported to be 3.5 %. In [5], ICA was applied on six 31.5 Ah NMC cells exposed to cycling aging at different cycle depths. The data was processed by Gaussian smoothing. Thereby several peaks and valleys were identified. Two peaks and valley correlated with the actual capacity, which could be used for SoH estimation with a maximum error of 2.5 %. In [6] three different NMC battery cells were exposed to cycling aging. The authors demonstrated that the SoH can be described by a 1st order polynomial with a normalized Incremental Capacity (IC) peak as input. The SoH estimation error achieved was below 3.1 %. In [7] NMC cells were exposed to calendar aging for different temperature and SoC condition. Six peaks and valleys were identified, which potentially gave twelve FPs as each peak or valley has a voltage and IC value. Only four out of the twelve FPs showed a good trend with the capacity fade, and a Goodness-of-Fit as high as 0.99 was achieved.

Since very promising results have been reported on SoH estimation based on ICA in the scientific literature [3]-[8], a natural next step would be to apply the ICA methods on real life applications, e.g. on EVs. To the best of our knowledge, the work for SoH estimation based on ICA method, which is proposed in the scientific literature, is mainly carried out in laboratory environments, where the temperature, rest time, etc. can be controlled. However, in a real-life usage, the battery temperature cannot be expected to be controlled in the same manner. Also, there will be cables, relays, fuses, etc. in the current path, which will create voltage drops as the charging current needs to have a certain amplitude in order to be practical feasible [9]. The battery-management-system of the car might balance the cells during operation meaning that there could be cell-to-cell variations with respect to SoC level, current, and temperature.

The purpose of this paper is therefore to evaluate whether the ICA method can be applied on commercial available EVs as a SoH estimation tool.

This paper is an extended version of [10] in which only results for the NMC type used for the BMWi3 EV were presented. In this work, besides the results for the NMC type, results for the Lithium Manganese Oxide (LMO) type, which is used for Nissan Leaf first generation EVs, have also been added. In addition, SoH estimation results have been added for both types on both cell and car level to demonstrate the usability of the ICA method. More specifically, this paper provide the following contributions:

- Evaluation of the ICA method as SoH estimation tool on car level in real-life conditions.
- Comparison of the ICA method for SoH estimation at cell level and car level.

II. METHODOLOGY

A. Battery data

In this work, NMC cells used in BMWi3 EVs and LMO cells used in Nissan Leaf EVs have been applied. Spare modules have been purchased and disassembled for both types. In Fig. 1 a spare module consisting of twelve series connected cells for the BMWi3 EV can be seen. The data of the battery cells and the conditions applied during charging and discharging of the cells can be seen in Table 1. The C-rate is the ratio of the actual current relative the nominal capacity. For example, if the nominal capacity is 63.0 Ah, the 0.5 C current is equal to 31.5 A.

Fig. 1: BMWi3 battery module being disassembled [10].

TABLE 1: DATA OF BMWI3/NISSAN LEAF EV BATTERY CELLS AND APPLIED CHARGE AND DISCHARGE CONDITIONS

Battery type	NMC	LMO
Nominal capacity	63 Ah	32.5 Ah
Maximum charging voltage	4.125 V	4.150 V
Minimum discharge voltage	3.000 V	2.500 V
Cut-off charging current (5 % of 1 C)	3.15 A	1.63 A
Charge rate	0.5 C	
Discharge rate	1.0 C	
Temperature	25ºC	

B. Aging test on cell level

In order to be able to evaluate the results on car level, aging test has been carried out on cell level in a controlled laboratory environment. Therefore, calendar aging test of six cells of each type have been conducted. During the calendar-aging test the cells are exposed to different temperature and SoC levels as seen in Table 2.

Each month the calendar aging test were interrupted and the capacity of the cells was measured by applying the charge and discharge conditions in Table 1.

TABLE 2: TEST MATRIX USED FOR CALENDAR AGING TEST FOR NMC AND LMO CELLS [10]

Temperature\SoC	10 %	50 %	90 %
7ºC		Cell 6	
35ºC		Cell 1	
40ºC		Cell 2	
45ºC	Cell 4	Cell 3	Cell 5

C. EV measurements

To investigate the usability of the ICA method on car level two different BMWi3 EVs and a first generation Nissan Leaf EV have been tested. The three cars have different mileage history, and therefore a difference is expected when the ICA-method is applied. The battery of all the cars are being drained as much as the cars allows. Before charging, the cars are parked inside a workshop in order to reach a constant and homogenous battery temperature of around 20ºC for more than 8 hours. The cars are being charged with a constant charging rate of 0.4

C (BMWi3) or 0.5 C (Nissan Leaf) until the maximum battery voltage is reached. Then the battery is charged in Constant Voltage (CV) mode. The cars are controlling the CV mode and the maximum current requested from the car to the charger is never violated at any time during the charging process.

The ICA method should in principle be applied on the open circuit voltage of the battery as the C-rate will affect the peak and valley locations [1], [9]. However, charging with a current close to zero is not a practical solution if the method should be practical feasible. The choice of C-rate is therefore a compromise between accuracy and speed. It is outside the scope of this paper to go into further detail regarding the selection of C-rate, but an initial investigation indicated that the 0.4 C and 0.5 C charging rate was an acceptable compromise between charging time and the distorting voltage drop across the resistive elements of the cars, i.e. resistance of the battery, cables, relays, etc.

D. *Data processing*

The ICA method has been applied on both cell level and car level. The Incremental Capacity (IC) is defined as the capacity q [Ah] differentiated with respect to the voltage v [V], i.e.

$$IC = \frac{dq}{dv} \approx \frac{\Delta q}{\Delta v}. \qquad (1)$$

The change in voltage has been kept fixed at $\Delta v =$ 40 mV and the corresponding change in capacity Δq [Ah] has then been calculated. The capacity is simply defined as the integration of the charging current i [A] during charging, i.e.

$$q = \frac{1}{3600} \int i dt. \qquad (2)$$

The choice of the voltage change Δv is a compromise between on one hand the prominence of the peaks and valleys and on the other hand the capability to suppress spikes or dips caused by random current changes due to the charger. It is out of the scope of this paper to go into further detail on this, but the 40 mV turned out to be a good compromise between the two considerations mentioned above.

Further more, in order to avoid jumps in the IC values, the voltage and capacity have been smoothed using a moving average filter with duration of 200 s before (1) has been applied. It should also be noticed that IC calculation is only applied during the constant current charging mode in order to avoid variation of the battery voltage due to the ohmic resistance of the current path.

III. RESULTS

A. *Results at cell level – NMC type*

The charging capacity and incremental capacity of the six NMC cells measured over 17 months can be seen in Fig. 2 to Fig. 7. As expected, the charging capacity becomes smaller, the longer storage time. It is also noticed that three peaks and valleys appear, and that there is a clear relationship in the evolution of Peak 1, Peak 2, Peak 3, and Valley 2 on the storage time. On the other hand, for Valley 1 and Valley 3, a clear evolution with respect to the storage time cannot be seen.

In order to be able to compare the peaks and valleys at cell level to the peaks and valleys on car level, a Partial Charging Capacity (PCC) ΔQ is defined between 3.60 V and 4.08 V, i.e.

$$\Delta Q = q(4.08\text{ V}) - q(3.60\text{ V}). \qquad (3)$$

A PCC is chosen as the complete charging capacity is based on the minimum and maximum voltage levels allowed by the car.

TABLE 3: NMC PCC AT MONTH 0 (M0) AND MONTH 17 (M17) AND THE CAPACITY FADE [10]

	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6
ΔQ(M0)	39.8 Ah	40.0 Ah	40.1 Ah	40.1 Ah	40.2 Ah	40.1 Ah
ΔQ(M17)	32.1 Ah	29.1 Ah	22.4 Ah	38.2 Ah	35.2 Ah	37.9 Ah
Cap. fade	19.4 %	27.3 %	44.1 %	4.7 %	12.4 %	5.5 %

As shown in Table 3, Cell 3 (Fig. 4) has lost 44.1 % of its PCC and is therefore the cell with the biggest capacity loss. In comparison to the other cells, a fourth peak and valley are appearing for some of the longest storage periods. Peak 1 and Valley 1 are however not present for long storage periods. This is in fact also seen for Cell 2 (Fig. 3), which is the cell with second biggest capacity loss. Peak 1 becomes weaker and weaker and eventually fade away. A remarkable behavior is also seen in Peak 2. For Cell 1-3, the voltage position of Peak 2 is mainly moving to the right, i.e. higher voltage values, the longer storage time, whereas as the IC values almost remains. However, for Cell 4 and 5, the voltage position is almost nearly the same, but the IC value become bigger for longer storage time. This means that the IC value of Peak 2 isn't a good SoH indicator as its location depend on the aging condition.

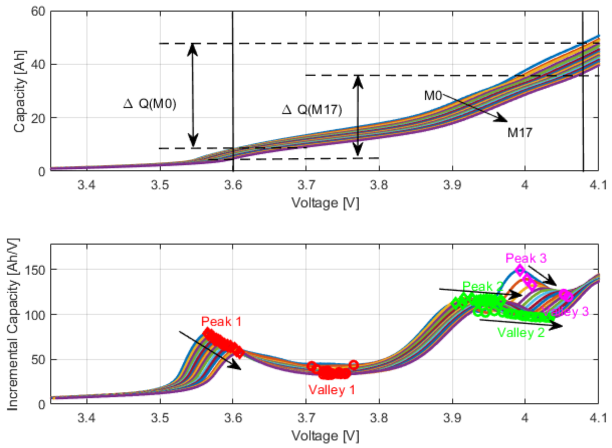

Fig. 2: NMC Cell 1 charging capacity (top) and incremental capacity (bottom) as function the charging voltage measured over 17 months. The arrows indicate the evolution from month 0 (M0) to 17 (M17) [10].

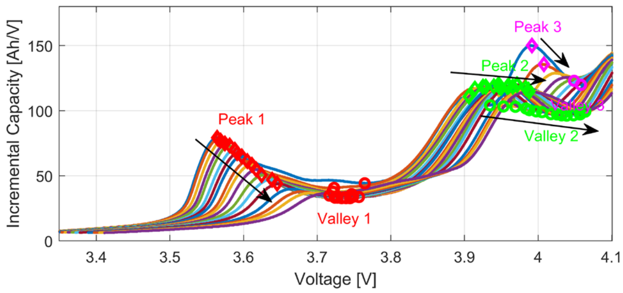

Fig. 3: NMC Cell 2 incremental capacity as function the charging voltage measured over 17 months. The arrows indicate the evolution from month 0 (M0) to 17 (M17) [10].

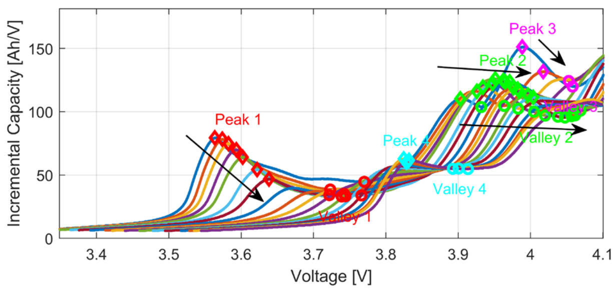

Fig. 4: NMC Cell 3 incremental capacity as function the charging voltage measured over 17 months. The arrows indicate the evolution from month 0 (M0) to 17 (M17) [10].

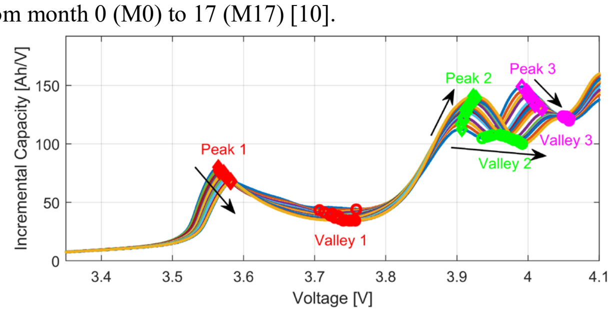

Fig. 5: NMC Cell 4 incremental capacity as function the charging voltage measured over 17 months. The arrows indicate the evolution from month 0 (M0) to 17 (M17) [10].

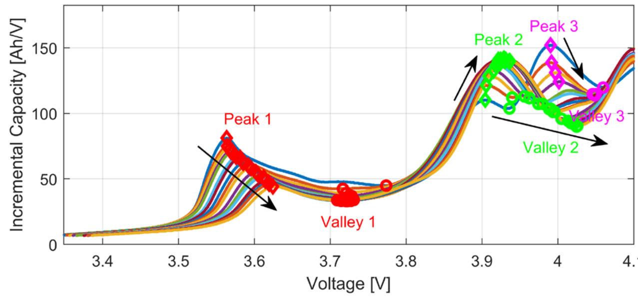

Fig. 6: NMC Cell 5 incremental capacity as function the charging voltage measured over 17 months. The arrows indicate the evolution from month 0 (M0) to 17 (M17) [10].

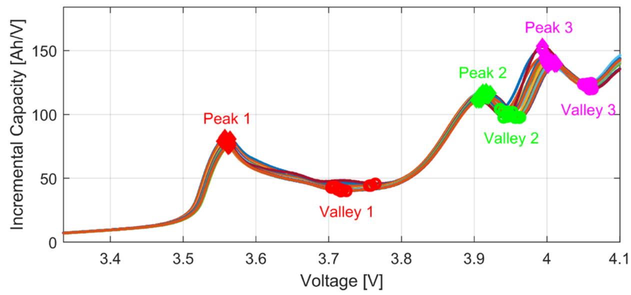

Fig. 7: NMC Cell 6 incremental capacity as function the charging voltage measured over 17 months. The arrows indicate the evolution from month 0 (M0) to 17 (M17) [10].

B. Results at car level – NMC type

Two different BMWi3 cars have been used for this investigation. The charging capacity and incremental capacity of the two cars (Car 1 and Car 2) can be seen in Fig. 8 and Fig. 9, respectively. The voltage has been scaled down by the number of series connected cells of the cars in order to be able to compare with the results of the six individual cells.

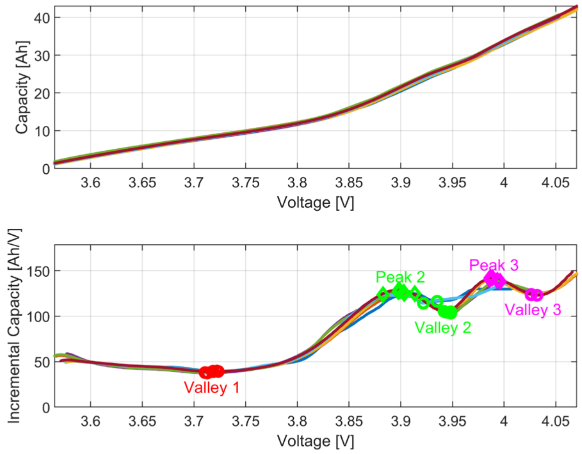

Fig. 8: BMWi3 Car 1 charging capacity (top) and incremental capacity (bottom) as function the charging voltage scaled to cell level [10].

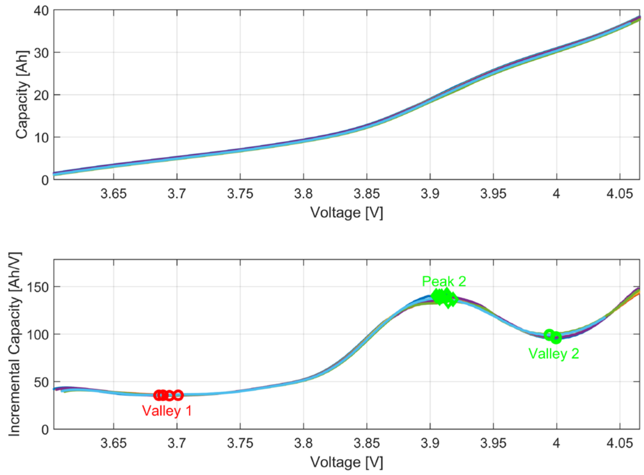

Fig. 9: BMWi3 Car 2 charging capacity (top) and incremental capacity (bottom) as function the charging voltage scaled to cell level [10].

First of all, it is noticed that the voltage interval is shorter than for the results at cell level. This is simply because the cars do not allow such low and high voltage limits which has been applied on the individual cells level. This means that the Peak 1 is not present on car level as the voltage position of Peak 1 is lower than the allowed minimum voltage of the car. Peak 1 therefore cannot be used as a SoH indicator. However, besides the shorter voltage interval, the IC on car level is similar to the one obtained on cell level.

The PCC at car level for NMC type is determined in the same way as for the cells, i.e. by (3). Car 1 (Fig. 8) has been measured seven times over a period of 17 days, and the mileage therefore only change from 13,223 km to 13,962 km. The average PCC of the five measurements is 41.0 Ah, and the maximum deviation of the five measurements to the mean is 1.3 %. The location of the peaks and valleys is consistent for the seven measurements, which indicates that the incremental capacity curve is reproducible for the same capacity. This is a requirement if the ICA method should be applied on car level.

Car 2 (Fig. 9) has been measured over a period of nine days. The mileage change from 39,105 km to 39,116 km, i.e. almost three times the miles as of Car 1. The average PCC is 39.2 Ah (with a maximum deviation from the average of 0.3 %), i.e. a capacity reduction of approx. 5 % in comparison to Car 1. It is however, unknown if this capacity reduction is because of the higher mileage or other factors, i.e. storage conditions. Neither Peak 3 nor Valley 3 are present. However, from the results at cell level, Peak 3 was disappearing for long storage time, i.e. reduced capacity, and Valley 3 was present around 4.05 V, i.e. at the border of the maximum allowed voltage at car level. The reduced capacity of Car 2 in compare to Car 1 therefore seems to affect the presence of Peak 3 and Valley 3. These therefore cannot either be used as a SoH indicator at car level.

C. SoH estimation using ICA method – NMC type

If the ICA method should be applied on car level, the location of the peaks and valleys at car level need to be the same as on cell level for the same capacity. The PCC of the NMC battery type due to the voltage and IC coordinates of Peak 1 and Peak 2 are shown in Fig. 10 at both cell and car level. The same has been done for Valley 1 and 2 in Fig. 11. It is noticed, that for the voltage coordinate of Peak 2 and voltage coordinate of Valley 2, good trends are seen with respect to the PCC. A 1st order polynomial curve fit is also shown, and it is also noticed that the results at car level are on the same line as the results at cell level. The voltage coordinate of Peak 2 however provide the highest goodness of fit (0.97). This feature point is therefore selected for SoH estimation, i.e.

$$\Delta Q_{\mathrm{estimation}} = 557.17 - 132.43 \cdot V. \qquad (4)$$

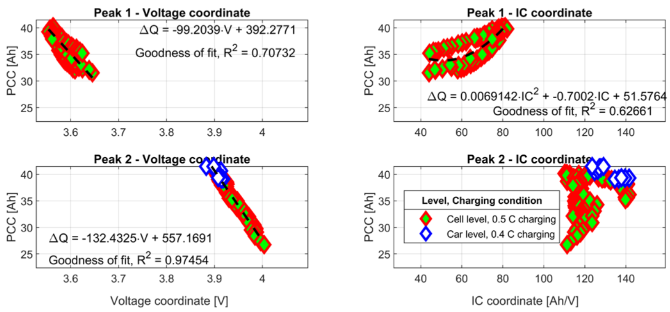

Fig. 10: Partial charging capacity shown as function of the Peak 1 (top) and Peak 2 (bottom) voltage coordinate (left) and IC coordinate (right) of NMC type at cell and car level.

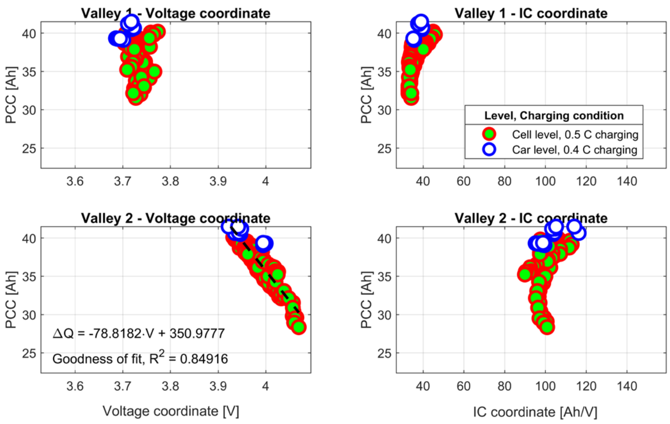

Fig. 11: Partial charging capacity shown as function of the Valley 1 (top) and Valley 2 (bottom) voltage coordinate (left) and IC coordinate (right) of NMC type at cell and car level.

The actual and estimated SoH are defined as the actual and estimated PCC relative to the maximum measured PCC, i.e.

$$SoH_{\text{actual}} = \frac{\Delta Q_{\text{actual}}}{\max(\Delta Q)} \times 100\ \% \tag{5}$$

$$SoH_{\text{estimation}} = \frac{\Delta Q_{\text{estimation}}}{\max(\Delta Q)} \times 100\ \%. \tag{6}$$

The SoH error is simply the difference between the estimated and actual SoH, i.e.

$$SoH_{\text{error}} = SoH_{\text{estimation}} - SoH_{\text{actual}}. \tag{7}$$

The actual and estimated SoH and the error is shown in Fig. 12. It is seen that the SoH error for both cell and car level is quite low (root-mean-square-error of 1.33 % and maximum error 4.25 %)

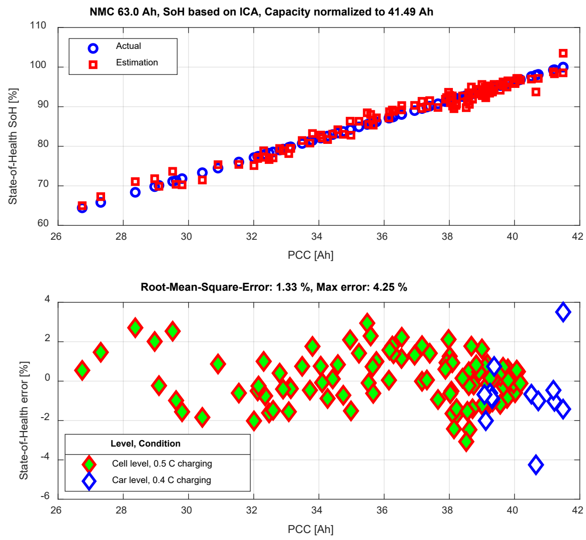

Fig. 12: Actual and estimated SoH normalized to the maximum PCC (top) and SoH error (bottom) for NMC type on both cell and car level.

D. *Results at cell level – LMO type*

The charging capacity and incremental capacity of the six LMO cells measured over 13 months can be seen in Fig. 13 to Fig. 18. As for the NMC cells, it can be seen that some of the peaks and valleys also show a clear evolution due to the aging. For most of the LMO results two peaks (Peak 1 and Peak 2) and valleys (Valley 1 and Valley 2) are present. A third peak seem to take form, but only the prominence for Cell 2 (Fig. 14), is strong enough to be identified as a Peak 3. Cell 6 (Fig. 18) is stored at low temperatures which result in only 4.1 % capacity fade. For this cell only a single peak (Peak 2) and valley (Valley 2) are present.

The PCC for the LMO battery cells are defined in the interval between 3.45 V and 4.08 V. i.e.

$$\Delta Q = q(4.08\text{ V}) - q(3.45\text{ V}). \tag{8}$$

As shown in Table 4, Cell 3 (Fig. 15) has lost 44.6 % of its PCC and is therefore the cell with the biggest capacity loss. It was also Cell 3 of the NMC cells which had the highest capacity loss. The applied aging condition of 50 % SoC at 45^{o}C is therefore the worst aging condition for both types of cells in this study.

TABLE 4: LMO PCC AT MONTH 0 (M0) AND MONTH 13 (M13) AND THE CAPACITY FADE

	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6
ΔQ(M0)	21.1 Ah	21.2 Ah	21.0 Ah	20.3 Ah	19.5 Ah	21.0 Ah
ΔQ(M13)	18.3 Ah	17.0 Ah	11.6 Ah	16.1 Ah	13.8 Ah	20.2 Ah
Cap. fade	13.0 %	20.1 %	44.6 %	20.6 %	29.3 %	4.1 %

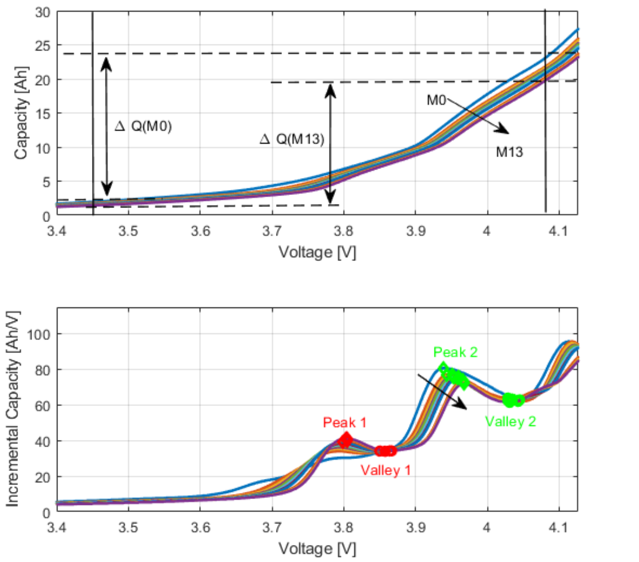

Fig. 13: LMO Cell 1 charging capacity (top) and incremental capacity (bottom) as function the charging voltage measured over 13 months. The arrows indicate the evolution from month 0 (M0) to 13 (M13).

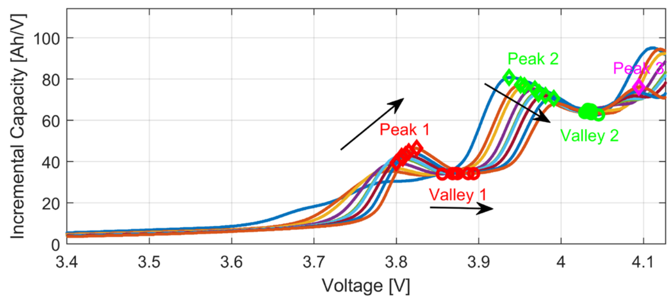

Fig. 14: LMO Cell 2 incremental capacity as function the charging voltage measured over 13 months. The arrows indicate the evolution from month 0 (M0) to 13 (M13).

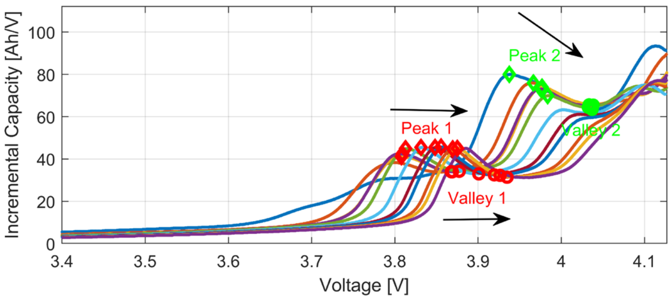

Fig. 15: LMO Cell 3 incremental capacity as function the charging voltage measured over 13 months. The arrows indicate the evolution from month 0 (M0) to 13 (M13).

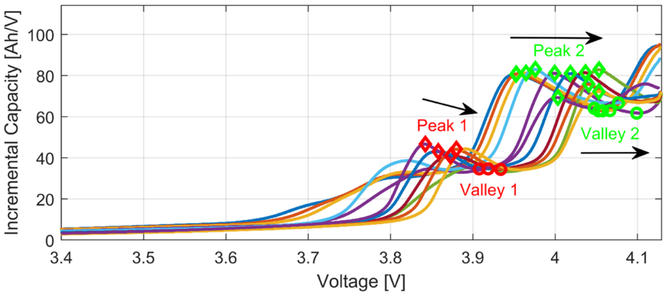

Fig. 16: LMO Cell 4 incremental capacity as function the charging voltage measured over 13 months. The arrows indicate the evolution from month 0 (M0) to 13 (M13).

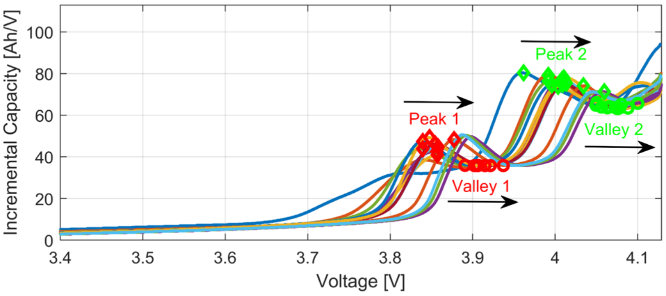

Fig. 17: LMO Cell 5 incremental capacity as function the charging voltage measured over 13 months. The arrows indicate the evolution from month 0 (M0) to 13 (M13).

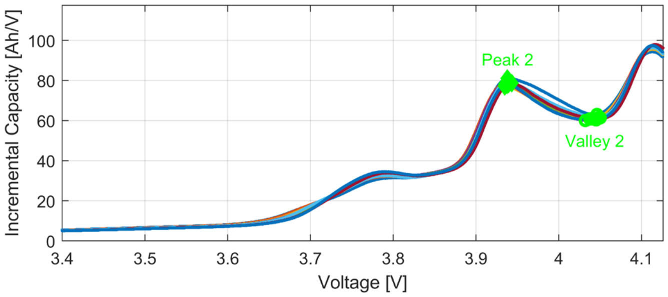

Fig. 18: LMO Cell 6 incremental capacity as function the charging voltage measured over 13 months. The arrows indicate the evolution from month 0 (M0) to 13 (M13).

E. *Results at car level – LMO type*

A Nissan Leaf EV has been used for this study. The charging capacity and incremental capacity of the car can be seen in Fig. 19. As for the BMWi3 cars, the voltage has been scaled down by the number of series connected cells of the car in order to be able to compare with the results of the six individual cells.

The PCC at car level for LMO type is defined in the same way as for cell level, i.e. by using (8). The Nissan Leaf EV has been measured two times over a period of 6 days, and the mileage therefore only change from 12,416 km to 12,567 km. The average PCC of the two measurements is 17.3 Ah.

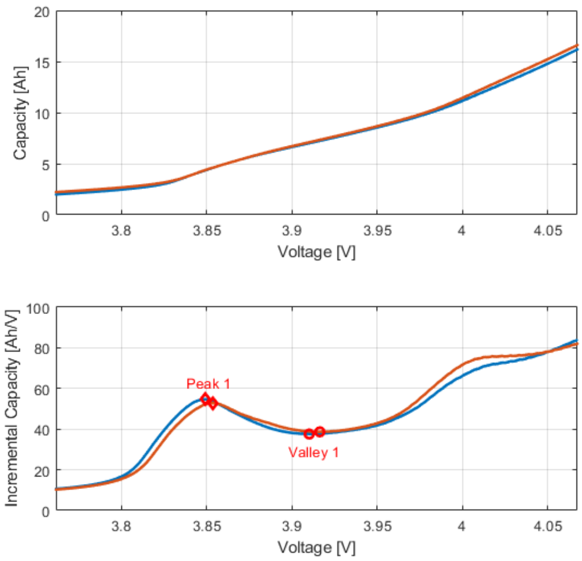

Fig. 19: LMO Nissan Leaf car charging capacity (top) and incremental capacity (bottom) as function the charging voltage scaled to cell level.

F. *SoH estimation using ICA method – LMO type*

As for the NMC type, the PCC are also shown as function of the voltage and IC coordinates of the peaks (Fig. 20) and valleys (Fig. 21). It is noticed, that only the voltage coordinates of Peak 1, Peak 2, and Valley 1 provide a sufficient relationship to the PCC. The voltage coordinate of Peak 2 give the best goodness of fit, but unfortunately, none Peak 2 are present at car level. Valley 1 provide the second best goodness of fit, and therefore this feature point is used for PCC estimation, i.e.

$$\Delta Q_{\text{estimation}} = 246.56 - 58.99 \cdot V. \qquad (9)$$

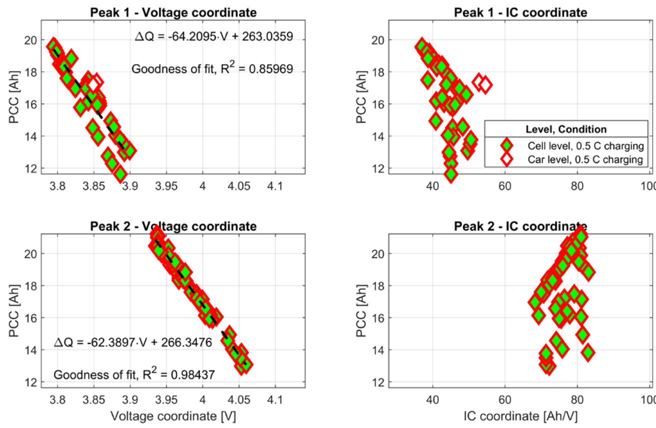

Fig. 20: Partial charging capacity shown as function of the Peak 1 (top) and Peak 2 (bottom) voltage coordinate (left) and IC coordinate (right) of LMO type at cell and car level.

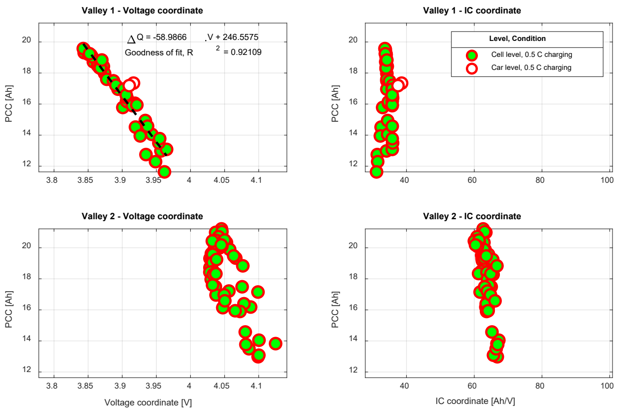

Fig. 21: Partial charging capacity shown as function of the Valley 1 (top) and Valley 2 (bottom) voltage coordinate (left) and IC coordinate (right) of LMO type at cell and car level.

The performance of the ICA method as a SoH estimation tool applied on the LMO types on both cell and car level can be seen in Fig. 22. It is noticed that the error on both cell and car level is higher than for the NMC types as the root-mean-square-error is 2.92 % and the maximum error is as high as 8.54 %. This could indicate that the applied C-rate at 0.5 C might be too high for the LMO types and require further investigation.

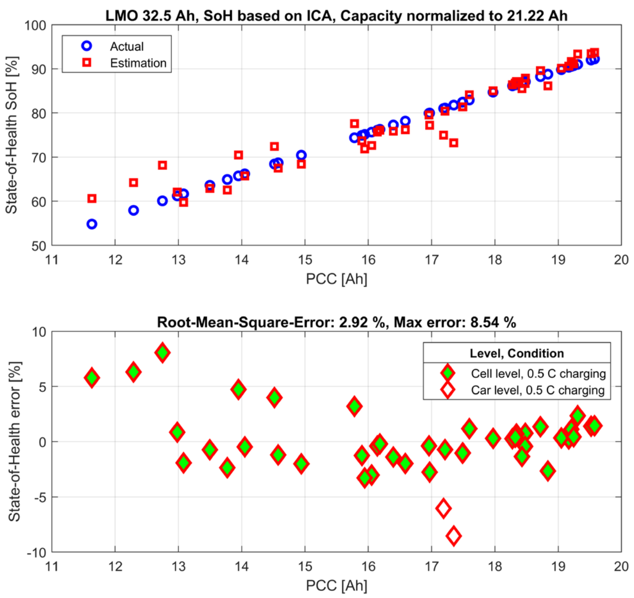

Fig. 22: Actual and estimated SoH normalized to the maximum PCC (top) and SoH error (bottom) for LMO type on both cell and car level.

IV. Discussion

In general there is a good match between the peak and valley coordinates at cell level and car level for both the NMC and LMO battery types. However, differences are also seen. One explanation could be that only calendar aging have been considered at cell level in this study, whereas the tested cars by nature also are being exposed to cycling aging. Cycling aging might affect the peak and valley coordinates in another way than pure calendar aging. A second explanation could be, that the car battery to some degree is considered as a black-box with no access points and it is not possible to measure or control the battery pack temperature in the same manner as on cell level. EV battery packs seem in general to have some thermal insulation but not all EVs have or activate active thermal management to equalize temperature differences and maintain stable battery conditions. For example, even though the cars have been acclimatized, the battery pack temperature may increase slightly in some cells during the charge process. Also, there might be internal auxiliary loads of the car while charging which cannot be monitored externally. This means that the actual current seen by the battery pack might be different from the terminal current fed into the cars.

V. Conclusion

In this work, the ICA method as a SoH estimation tool for EVs has been investigated. The study is based on NMC cells used in the BMWi3 EV and LMO cells used in the Nissan Leaf EV. Test has been applied on both cell level and car level. Characteristic peaks and valleys are appearing when performing ICA. These peaks and valleys can be used for SoH estimation. The peak and valley locations on car level are consistent. It is also shown that the peak and valley location on cell level matches with the peak and valley location on car level for the same PCC. The cars however does not allow deep discharge levels nor high charging voltage levels, and some of the peaks and valleys present at cell level therefore disappears at car level. The SoH estimation applied on the NMC type resulted in root-mean-square-error of 1.33 % and 2.92 % for the LMO type, whereas the maximum error was 4.25 % for the NMC type and 8.54 % for the LMO type. It has therefore been demonstrated that the ICA method is applicable on car level for battery SoH estimation, but for this particular study, the NMC battery type provide better results than the LMO type.

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